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What is adaptive about adaptive decision making? A parallel constraint satisfaction account ☆

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ABSTRACT

There is broad consensus that human cognition is adaptive. However, the vital question of how exactly this adaptivity is achieved has remained largely open. Herein, we contrast two frameworks which account for adaptive decision making, namely broad and general single-mechanism accounts vs. multi-strategy accounts. We propose and fully specify a single-mechanism model for decision making based on parallel constraint satisfaction processes (PCS-DM) and contrast it theoretically and empirically against a multi-strategy account. To achieve sufficiently sensitive tests, we rely on a multiple-measure methodology including choice, reaction time, and confidence data as well as eye-tracking. Results show that manipulating the environmental structure produces clear adaptive shifts in choice patterns – as both frameworks would predict. However, results on the process level (reaction time, confidence), in information acquisition (eye-tracking), and from cross-predicting choice consistently corroborate single-mechanisms accounts in general, and the proposed parallel constraint satisfaction model for decision making in particular.

1. Introduction

One of the most well-established notions about human behavior and thought is that both are somehow adapted to the environment (Brunswik, 1956) and "[t]he view of Homo sapiens as an adaptive decision maker has continued to receive support" (Weber & Johnson, 2009, p. 76). Indeed, the question of which behavior may be considered rational has long been argued to depend on the environment and the goals of the organism or agent (Chater, Oaksford, Nakisa, & Redington, 2003; Simon, 1956) and it has been investigated how empirically verifiable principles of human cognition "can be viewed as arising from the rational adaptation of the cognitive system to the problems and constraints that it faces" (Chater & Oaksford, 2000, p. 107). One of the most basic of these problems we face is the necessity to make accurate inferences in a fundamentally uncertain world providing only probabilistic information or cues (Brunswik, 1952; Gigerenzer, Hoffrage, & Kleinbölting, 1991) that may vary in validity across different environments. The major challenge for research is thus to understand how decision makers adapt to this variation.

In what follows, we pose the question what exactly is adaptive about adaptive decision making. More specifically: How do decision makers react to different environmental structures appropriately when relying on probabilistic cues to draw inferences? At the level of theoretical frameworks, these questions have been tackled by two distinct approaches: (a) by proposing broad models of cognition

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which specify a general mechanism that can apply to many tasks, domains, and environments (e.g., Busemeyer, Pothos, Franco, & Trueblood, 2011; Busemeyer & Townsend, 1993; Dougherty, Gettys, & Odgen, 1999; Fiedler, 2000; Lee & Cummins, 2004; Newell, 2005) or (b) by assuming a repertoire of more or less specialized cognitive tools, many of which are optimally suited for a narrow set of situations only (e.g., Beach & Mitchell, 1978; Gigerenzer, Todd, & The ABC Research Group, 1999; Payne, Bettman, & Johnson, 1993; Scheibehenne, Rieskamp, & Wagenmakers, 2013). Concerning the adaptation to varying environments when drawing probabilistic inferences, these two frameworks differ as follows: In the former "single-mechanism" view, decision makers differ in the weighting of the cues fed into the *same* system and thus generally make decisions based on a single mechanism of information integration. In the latter "multi-strategy" view, by contrast, decision makers select qualitatively *different strategies* for different environments and thus rely on distinct mechanisms.

Herein, we put forward a general single-mechanism model for probabilistic inferences that is based on a connectionist parallel constraint satisfaction approach to cognition (see McClelland et al., 2010; Read, Vanman, & Miller, 1997; Rumelhart, Hinton, & McClelland, 1986, for overviews). Corresponding models have been successfully applied to account for phenomena in a broad range of domains including perception (McClelland & Rumelhart, 1981), analogies (Holyoak & Thagard, 1989), impression formation (Kunda & Thagard, 1996), preference construction (Simon, Krawczyk, & Holyoak, 2004), legal reasoning (Holyoak & Simon, 1999; Simon, Snow, & Read, 2004), and person construal (Freeman & Ambady, 2011). More specifically, we generalize and extend previous accounts (Betsch & Glöckner, 2010; Glöckner & Betsch, 2008a; Holyoak & Simon, 1999) and put forward a fully specified parallel constraint satisfaction model for adaptive decision making that can accommodate individual differences in information integration. We then contrast this model theoretically to the multi-strategy approach and finally tease the two apart empirically in a set of experiments by investigating their capabilities to predict choices, decision time, and confidence on the level of individuals as well as general patterns of information search.

2. Single-mechanism models of decision making and the parallel constraint satisfaction model

Broad models of cognition typically aim to explain adaptivity by specifying plausible cognitive mechanisms that approximate rational solutions (e.g., Hintzman, 1984; Kruschke, 1992). The idea is that "[f]ormal rational principles spell out the optimal solution" and "well-adapted agent[s] will approximate this solution to some degree" (Chater & Oaksford, 2000, p. 112). One class of broad single-mechanism theories of cognition that approximate rationality through mechanisms taking into account (and weighting) all evidence, are random-walk or diffusion models (e.g., Busemeyer & Townsend, 1993; Diederich, 2003; Krajbich & Rangel, 2011; Lee & Cummins, 2004; Ratcliff & McKoon, 2008; Usher & McClelland, 2001). In simple terms, their basic idea is that information is sampled continually and evidence accumulated over time until a certain threshold is researched and it is exactly this threshold which constitutes the adaptive component of these models. As a vivid metaphor, Newell (2005) coined the term of an "adjustable spanner" to reflect the idea of a single tool (or cognitive mechanism) which achieves flexibility through adaptively setting an evidence-threshold.

One common feature of these models is the assumption of unidirectional reasoning from information to decisions, implying that information in itself is accumulated but that its' evaluation is not changed in the decision process. In connectionist implementations of these evidence accumulations models (e.g., Busemeyer, Jessup, Johnson, & Townsend, 2006; Busemeyer & Johnson, 2004; Usher & McClelland, 2001, 2004) this is usually reflected in unidirectional spread of activation. However, the assumption of unidirectional reasoning has been challenged in several domains, especially in light of *coherence effects*, that is, systematic shifts in how information is evaluated *within* the decision process (i.e., before a decision is made) to support the emerging favored decision (e.g., Bond, Carlson, Meloy, Russo, & Tanner, 2007; Brownstein, 2003; Brownstein, Read, & Simon, 2004; Carlson & Russo, 2001; DeKay, Patino-Echeverri, & Fischbeck, 2009; Glöckner, Betsch, & Schindler, 2010; Holyoak & Simon, 1999; Russo, Medvec, & Meloy, 1996; Simon, Snow, et al., 2004). As such, bidirectional reasoning has found substantial support.

Correspondingly, bidirectional reasoning is a core property of connectionist parallel constraint satisfaction networks (McClelland & Rumelhart, 1981; Thagard, 1989, 2000). Their general idea follows in the Gestalt tradition of psychology by assuming a cognitive system which minimizes informational conflict to form a coherent mental representation of the problem at hand, simultaneously taking into account bottom-up (e.g., observed cues) and top-down (e.g., conceptual knowledge) influences (see also Clark, 2013). One such theory is the parallel constraint satisfaction (PCS) model by Glöckner and Betsch (2008a). Therein, it is assumed that processes of decision making can be modeled by spreading activation mechanism in relatively simple symbolic networks. The PCS model describes fast, automatic processes that lead to consistent mental representations of the task and intuitive choices that emerge without awareness of the process itself (Glöckner & Witteman, 2010). According to PCS, the initial process automatically attempts to make sense of the available information. External information is combined with information from memory and spreading activation mechanisms are applied to form the most coherent mental representation given logical constraints within this set of information. If the resulting mental representation is highly coherent, clearly indicating that one option is better than the other(s), a decision is instantly made without further deliberation. If coherence is below a certain threshold, deliberate processes are additionally activated.

In a probabilistic inference task, networks in the model consist of two layers of nodes representing options (second layer) and cues (first layer) that provide information concerning the options on the relevant criterion (see also Fig. 1). Bidirectional links between nodes capture mutual coherence or conflict between the represented concepts.